International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 13, Issue 8, August 2024)

Survey of AI Techniques for Underwater Image Color Restoration

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***Abstract*— Underwater image color restoration is a critical task in marine exploration, underwater archaeology, and aquatic environmental monitoring. The underwater environment poses significant challenges for image acquisition due to the absorption and scattering of light, leading to color distortion, reduced contrast, and blurring. Traditional image processing techniques often fall short in addressing these issues comprehensively. This survey provides an extensive review of the current state-of-the-art artificial intelligence (AI) techniques applied to underwater image color restoration.**

Keywords*— *Artificial Intelligence, Underwater, Image, Color, Restoration.

I. Introduction

Underwater imaging plays a pivotal role in various scientific and commercial applications, including marine biology, underwater archaeology, and environmental monitoring. However, capturing high-quality images underwater is inherently challenging due to the unique properties of the aquatic environment. The absorption and scattering of light by water and its constituents cause significant degradation in image quality, manifesting as color distortion, reduced visibility, and loss of contrast. These issues complicate the interpretation and analysis of underwater images, necessitating advanced restoration techniques to retrieve accurate visual information.

Traditional methods for underwater image enhancement, such as histogram equalization and contrast stretching, have been employed with limited success. These methods often lack the sophistication to address complex distortions comprehensively and may introduce artifacts or fail to generalize across different underwater conditions. In response to these limitations, artificial intelligence (AI) has emerged as a powerful tool for underwater image color restoration. AI techniques, particularly those based on deep learning, have shown remarkable performance in enhancing image quality by learning from vast amounts of data and capturing intricate patterns of degradation and restoration.

This survey aims to provide a comprehensive overview of the AI techniques utilized for underwater image color restoration. We begin by discussing the fundamental challenges of underwater imaging and the inherent limitations of traditional enhancement methods. Subsequently, we delve into the AI-based approaches, categorizing them into supervised learning, unsupervised learning, and hybrid methods. Supervised learning techniques leverage labeled datasets to train models that can predict the restored color of degraded images. In contrast, unsupervised learning methods rely on intrinsic properties of the images to guide the restoration process without the need for labeled data. Hybrid approaches combine the strengths of both supervised and unsupervised learning to achieve superior performance.

Key contributions to the field include the development of convolutional neural networks (CNNs), generative adversarial networks (GANs), and other deep learning architectures tailored for underwater image restoration. These models have demonstrated significant improvements in color accuracy, contrast enhancement, and detail preservation. We also examine the role of machine learning algorithms, such as support vector machines (SVMs) and random forests, which have been integrated with deep learning frameworks to enhance restoration outcomes.

In addition to reviewing AI techniques, this survey highlights essential datasets and evaluation metrics that have been employed to benchmark the performance of restoration algorithms. Datasets such as the EUVP (Enhancement of Underwater Visual Perception) and UFO-120 (Underwater Image Quality Assessment) provide diverse and challenging images for training and testing. Evaluation metrics, including peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mean squared error (MSE), offer quantitative measures to assess restoration quality.

II. LITERATURE SURVEY

J. Lu et al. [1,] in order to ascertain the actual color of the picture. A neural network encoder is first applied to the input picture of an underwater scene in order to extract features from the image. This is done in order to accomplish the first step. Secondly, the use of three distinct decoders allows for the generation of estimates for the direct light transmission map, the backscattered light transmission map, and the veiling light. Third, the loss functions and the training technique have both been established in order to improve the efficiency of the restoration process. This was done in order to make the procedure more efficient. It is general information that the learning-based technique would need the use of a data collection that is comprised of paired instances for the training phase. Within the scope of this study, we also propose a method for the fabrication of underwater photos.

H. Wang et al., [2] photos are plagued by a number of degradation phenomena, such as poor contrast, fuzzy features, and color deviation, all of which pose a significant barrier to the development of relevant fields of study. As a consequence of this, scholars have been devoting an increasing amount of attention to the subject of how to repair and restore underwater photographs that have degraded via the use of post-production algorithms. In recent years, there has been a rapid expansion of technology linked with deep learning, which has resulted in substantial breakthroughs in the repair and restoration of underwater photos using deep learning. These developments have caused tremendous progress in the field.

G. Ramkumar et al., [3] The area of digital image processing is increasing on a daily basis as a result of the development of breakthrough technologies that have the potential to support a wide range of applications. In addition to a wide range of other uses, these applications include robotic initiatives and the creation of subsea networks. As a result of the movement of light waves that are not in the exact and predicted range under the water level, the process of underwater image processing is considered to be the most essential effort in the field of image processing. This occurs due to the fact that light waves have a distinct behavior when they travel through water.

S. Wu et al. [4] developed a two-stage underwater enhancement network that would consist of a preliminary enhancement network and a refinement network respectively. This design would be implemented in the underwater environment. It is advised that the preliminary enhancement network be created during the first stage. This network should include both the high-frequency enhancement networks and the low-frequency enhancement networks included in its composition. In contrast, the low-frequency enhancement network is based on underwater imaging, which combines an integrated transmission map and background light into a joint component map. The high-frequency component is enhanced directly by a deep learning network, while the low-frequency enhancement network incorporates underwater photography. In the second stage of the process, the refinement network is used. This network's objective is to further enhance the color of the underwater image by taking into account the complexities of underwater photography.

According to Y. Lu et al., [5] the purpose of this study is to discover a method that can totally eradicate speckle noise without seeing it. The multiplicative relationship that was previously present between the latent sharp image and the random noise will first be transformed into an additive form by means of a logarithmic transformation. This transformation will take place. The multi-scale mixed loss function has been proposed as a possible approach in order to further improve the robust generalization that was offered by DSPN et al. The

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deep blind despeckling network that was described is able to retain essential picture information while also reducing the amount of random noise that is present in the image.

Y. Lin et al. [6] divides the process of restoration into two distinct parts: horizontal distortion restoration and vertical distortion restoration. When it comes to dealing with horizontal distortion, it is recommended that a model-based network be used in the first phase of the production process. In order to achieve this goal, the undersea physical model would be immediately included into the network via direct integration. Calculating the attenuation coefficient, which is a feature representation in defining water type information, is the first step in the process of ensuring that the parameters in the physical model are estimated accurately.

Deep learning algorithms for photo dehazing have reached a more mature level, become more trustworthy, and shown exceptional performance, according to R. Liu et al. [7]. However, despite this, these methods are very dependent on the data that is used for training, which restricts the range of applications that can be carried out with them. More importantly, both traditional learning methods and deep learning approaches fail to address a widespread issue, which is the fact that noises and artifacts are constantly present throughout the process of recovery. The formation of Hadamard-product-based propagations takes place inside the learnable framework that we have constructed for the aim of image dehazing.

Y. Pei et al., [8] deep learning neural networks, and more specifically Convolutional Neural Networks (CNNs), have been instrumental in the advancement of the science of photo classification, which has become more important. This achievement is comparable to the achievements that have been achieved in a great number of other areas of computer vision. Image databases such as Caltech-256, PASCAL VOCs, and ImageNet are examples of the kinds of research that have been conducted in this field. The bulk of the efforts that have been made in this area have focused on the categorization of natural photographs that are quite clear. In many actual applications, however, the photos that are gathered may have specific degradations that lead to a range of various sorts of blurring, noise, and distortions. These degradations may be caused by a number of different factors.

Z. Wang et al., [9] Even if there is a continuous loss of resources on land, human exploration of the ocean has been increasing at a consistent pace. When it comes to gaining an understanding of the circumstances that exist below the water, one of the most basic methods is to visually see the ocean bottom from below. Underwater photographs, on the other hand, are subject to significant degradation as a consequence of the complex imaging environment of the ocean as well as the illumination scattering that takes place in the sea. As a result, it is hard to discern between information that is effective and information that is not effective. Because of this, there is a need for enhancements to be made to the capabilities of imaging underwater. Particularly when compared to more traditional procedures (such the histogram equalization method) and modeling methods, deep learning has been effectively used in the field of computer vision.

E. Silva et al., [10] The rapid growth in computer and sensor capacity has made it feasible to develop image restoration technologies that are suitable to underwater photography. These technologies have been successfully implemented. When it comes to applications that include robotic vision, water offers a considerable obstacle because of the high degree of absorption that it has. In order to fulfill the requirements of a wide variety of applications for underwater robots, a depth map is necessary, which offers a significant difficulty.

III. Assessment

Importance of Underwater Imaging

Underwater imaging is crucial for a variety of scientific and industrial applications, including marine biology research, underwater archaeology, environmental monitoring, and commercial activities such as underwater inspections and resource exploration. High-quality underwater images are essential for accurate analysis and interpretation, enabling researchers and professionals to observe and document underwater environments, species, and phenomena. However, capturing clear and color-accurate images underwater is a significant challenge due to the unique and adverse optical properties of water.

Challenges in Underwater Imaging

The underwater environment poses several challenges for image acquisition. Water absorbs and scatters light, especially in the red and green wavelengths, resulting in color distortion, reduced contrast, and blurriness. Suspended particles and plankton further degrade image quality by scattering light, creating a hazy appearance. These optical distortions complicate the task of extracting meaningful information from underwater images, making it difficult to identify and analyze underwater objects and scenes accurately.

Limitations of Traditional Enhancement Methods

Traditional image enhancement techniques, such as histogram equalization, contrast adjustment, and dehazing, have been applied to improve underwater images. While these methods can offer some degree of enhancement, they often fall short in addressing the complex and varied nature of underwater distortions. These techniques may improve certain aspects of an image while failing to correct color distortions or introducing new artifacts. Moreover, traditional methods lack adaptability and may not generalize well across different underwater conditions, limiting their effectiveness.

Emergence of AI Techniques

Artificial intelligence (AI) and machine learning, particularly deep learning, have shown great promise in overcoming the limitations of traditional methods. AI-based techniques can learn complex patterns and relationships within the data, enabling them to perform more sophisticated image restoration tasks. Convolutional neural networks (CNNs), generative adversarial networks (GANs), and other deep learning models have been successfully applied to underwater image restoration, achieving significant improvements in color correction, contrast enhancement, and detail preservation. Despite these advancements, challenges remain in developing robust and generalizable models that can handle diverse underwater conditions and provide consistent, high-quality results.

Need for Comprehensive Survey

Given the growing interest and progress in applying AI to underwater image restoration, there is a need for a comprehensive survey that systematically reviews and evaluates the existing techniques. Such a survey should highlight the strengths and limitations of various approaches, identify key datasets and evaluation metrics, and provide insights into emerging trends and future research directions. By consolidating current knowledge and advancements in the field, this survey aims to guide researchers and practitioners in developing more effective and reliable AI-based solutions for underwater image color restoration.

IV. CONCLUSION

Underwater image color restoration is a complex challenge due to the inherent optical distortions of the aquatic environment, which lead to significant color and contrast degradation. While traditional enhancement methods offer some improvements, they often fall short in effectively addressing the diverse and intricate distortions. The application of artificial intelligence (AI), particularly deep learning techniques such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), has significantly advanced the field by providing more accurate and adaptable restoration solutions. Despite these advancements, ongoing research is needed to enhance model robustness and generalization. Consolidating current knowledge and integrating emerging trends will be crucial for developing more effective underwater image restoration methods, ultimately improving the quality and utility of underwater imaging in various scientific and commercial applications.

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